The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance

Zheng Sun

Ashley Wang

Lu Zheng

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Abstract

Presumably, hedge fund managers pursue unique strategies because they have great new ideas and superior investment skills, while less skilled managers are more likely to herd and follow publicly known investment strategies. For investors, knowing how innovative and skillful their managers are is thus extremely important but very difficult because of the opaque nature of hedge fund operations. In this paper, we construct a measure of the distinctiveness of a fund's investment strategy based on historical fund return data. Specifically, we examine the extent to which a fund's returns differ from those of its peer funds. We term the measure "Strategy Distinctiveness Index" (*SDI*). The higher the *SDI*, the more distinctive is a fund's strategy. We document a substantial cross-sectional variation as well as strong persistence over time in funds' *SDI*. Our main result indicates that, on average, higher *SDI* is associated with better subsequent performance. Funds in the highest *SDI* quintile significantly outperform funds in the lowest *SDI* quintile by about 4 percent over the subsequent year.

I. Introduction

Investors pay high fees to hedge funds for their unique investment ideas and strategies. When an investment idea becomes known to a large number of investors, the abnormal return from the strategy is likely to be competed away. This, together with the well-documented finding of large performance variations across hedge funds, suggests that identifying fund managers with unique investment ideas is crucial for hedge fund investors. Nevertheless, the task is very challenging. First of all, hedge funds trade and operate with great secrecy and little disclosure in order to protect their investment ideas. Second, the rapid growth of the hedge fund industry has resulted in a wide range of strategies and a huge number of funds run by managers with diverse investment backgrounds and qualifications. In this paper, we make a first attempt to estimate the uniqueness and distinctiveness of a fund's investment strategy using historical hedge fund return data. We further examine whether a more distinctive investment strategy is indicative of greater managerial talents, and hence, superior fund performance.

Presumably, skilled hedge fund managers pursue distinctive strategies because they have great new ideas and superior investment skills, while less skilled managers are more likely to herd and follow publicly known investment ideas. We refer to this as the skill hypothesis. Consistent with this hypothesis, we would expect funds with skilled managers to pursue more innovative strategies and to deliver performance that is more distinctive from their peers. As a result, we should observe a positive relation between the distinctiveness in fund strategy and fund performance.

On the other hand, hedge fund managers may also appear to deviate from their peers if they take on excessive risk due to a potential conflict of interest between fund managers and investors. As Goetzmann, Ingersoll, and Ross (2003) show, the option-like characteristics of the compensation contract could provide incentives for managers to make idiosyncratic bets to increase the chance of extreme performance. We refer to this as the gaming hypothesis. Consistent with this hypothesis, funds pursuing such gaming strategy would appear to be distinctive from the peers. However, in this case, we should not observe a positive relation between future fund performance and the distinctiveness in fund strategy.

To study the distinctiveness of a fund's investment strategy, we propose a measure based on historical fund returns. Specifically, we examine the correlation of individual hedge fund returns with the average returns of peer funds in the same style category. In this context, we term (1-correlation) the "Strategy Distinctiveness Index" (*SDI*). *SDI* measures the extent to which a fund's returns differ from those of its peers. The higher the *SDI*, the more distinctive is the fund's investment strategy. We then examine how *SDI* relates to fund performance and other fund characteristics.

We define fund investment styles by clustering historic returns using a procedure similar to that in Brown and Goetzmann (1997, 2003). The clustering method groups funds to its closest cohort by minimizing the sum of the distance of all funds to the corresponding clusters. The partition of funds is based on a systematic and quantitative approach rather than predefined categories. As suggested by Brown and Goetzmann (1997, 2003), the statistical approach precludes possible misclassification of fund styles due to strategic self-reporting. The clustering method also allows time varying groupings as some funds may change investment strategies over time.

Using monthly return data on about 3600 hedge funds covered by Lipper TASS database over the period of January of 1994 to December of 2008, we construct the Strategy Distinctiveness Index (*SDI*) for individual funds. For the sample of funds, we control for survivorship and backfill biases to the extent the data allow. We document a substantial cross-sectional variation in *SDI*, indicating that some funds follow innovative investment strategies while others tend to herd. We also find strong persistence in individual fund *SDI* over time. This suggests that *SDI* is likely driven by fund characteristics, such as managerial innovation skills, that tend to be persistent over time, rather than by noise or by random bets prompted by a manager's gaming motive that are likely to be transitory.

We further study the determinants of *SDI*. We find that *SDI* is related to a number of fund characteristics. Specifically, *SDI* increases with lagged performance measures including risk adjusted returns, appraisal ratio, and the Sharpe ratio. This result is consistent with the skill hypothesis that *SDI* is related to better fund performance. Moreover, *SDI* decreases with the lagged idiosyncratic volatility of fund returns. This result is inconsistent with the gaming hypothesis that the deviation captured by *SDI* is driven by managers making random bets and taking on excessive risk to maximize the option-like payoff. Furthermore, we find that *SDI* decreases with fund age, size, length of lock up period, high water mark provision dummy, and increases with redemption notice period, fund incentive fees, past flows, minimum investment, and leverage usage dummy.

Our main test concerns the relation between *SDI* and fund performance. We form portfolios of hedge funds based on their *SDI* levels and examine the subsequent performance of these portfolios. Consistent with the skill hypothesis, we find that the *SDI* helps predict future fund performance. Funds with more distinctive strategies tend to perform consistently better after adjusting for differences in their risks and styles. Specifically, with a three-month sorting and annual holding trading strategy, the equally weighted quintile portfolio of funds with the highest lagged *SDI* yields an average risk adjusted return of 7.95 percent per year, whereas that with the lowest *SDI* yields 4.00 percent per year. The return difference between the two portfolios is statistically and economically significant.

Since the post-formation portfolio performance can only be measured based on funds that are present in the data set till the end of the holding horizon, the performance based on these existing funds may be biased. To examine whether the out-performance of the high *SDI* portfolio we have documented is mainly attributed to the difference in the drop-out rate, we analyze the drop-out property of the *SDI* portfolios. We find about 4% difference in the survival rate between the lowest *SDI* quintile portfolio (84%) and the highest quintile (80%) one year after the formation. We show through back-of-envelope calculations that the differences in the drop-out rate and the potential return bias are unlikely to explain away the out-performance of the high *SDI* portfolio.

We further examine the robustness of the above relation using a multivariate regression approach. Specifically, we use both pooled regressions with clustered standard errors and time and style fixed effects as well as Fama-MacBeth regressions with HAC standard errors. Controlling for other fund characteristics, we confirm the positive relation between a funds's *SDI* and its subsequent performance in the multivariate regression setting.

We also investigate whether our results hold up to alternative specifications for strategy distinctiveness. First, to ensure that our results are not specific to the cluster classification, we consider (1-correlation) using the TASS styles, termed as *SDI*(TASS). Then, we consider the $(1 - R^2)$ of a regression of individual hedge fund returns against the average returns of all peer funds: $(1 - R^2)$ captures the percentage of total variance in fund returns that cannot be explained by the returns of all peer funds. The overall pattern in these results again confirms that the more distinctive the strategy, the better future performance.

The remainder of the paper is organized as follows. Section II discusses the related literature. Section III introduces data. Section IV describes the construction of *SDI* (Strategy Distinctiveness

Index), its properties and determinants. Section V presents the empirical findings on the relation between *SDI* and future fund performance measures and robustness analysis. Section VI concludes.

II. Related Literature

Academic research shows that hedge funds follow dynamic investment strategies and have volatile returns. The empirical findings also largely indicate that hedge funds deliver positive alpha, while the evidence on performance persistence has been rather mixed. Some recent papers on fund performance include Ackermann, McEnally, and Ravenscraft, (1999) Agarwal and Naik (2000 and 2004), Brown, Goetzmann and Ibbotson (1999), Brown and Goetzmann (2003), Brown, Goetzmann, Liang and Schwarz (2007), Fung and Hsieh (1997, 2000, 2001, 2002), Goetzmann, Ingersoll and Ross (2003), Ibbotson and Chen (2006), Jagannathan, Malakhov and Novikov (2006), Kosowski, Naik and Teo (2007) and Liang (1999, 2000). Griffin and Xu (2007) analyze hedge fund disclosed holdings and find only weak statistical evidence for a better stock picking ability when comparing hedge funds to mutual funds.

Although hedge funds, as a group, deliver positive risk-adjusted returns and diversification benefits, large cross-sectional variations in hedge fund returns have also been documented by researchers, for example, Malkiel and Saha (2005). Despite the importance of distinguishing skilled hedge funds from the unskillful ones, research on the cross-sectional determinants of hedge fund returns has been rather limited until a few recent papers started to link hedge fund performance to various fund and managerial attributes. Aragon (2007) finds that funds with more stringent share restriction clauses offer an excess return of 4-7% per year. Aggrawal and Jorion (2009) document strong outperformance by emerging hedge fund managers especially during the first two to three years of fund existence. Agarwal, Daniel, and Naik (2007) show that funds with greater managerial incentives and discretion display superior performance. Li, Zhang and Zhao (2007) find that the educational background and working experience of managers are related to hedge fund performance. Titman and Tiu (2008) postulate that the ability to hedge systematic risk factor exposures reflects managerial talent. They find hedge funds that exhibit lower *R*-squares with respect to systematic factors have better performance. Related to this line of research, our paper takes a first attempt to study the innovativeness aspect of managerial talents and the distinctiveness of fund strategies.

The existing literature examining the effect of the innovativeness of managerial talents and distinctiveness of fund strategy on fund performance has been primarily focused on the mutual fund sector. Kacperczyk, Sialm, and Zheng (2005) argue that mutual fund managers may decide to deviate from a well-diversified portfolio and concentrate their holdings in industries where they have informational advantages. Their results confirm that more concentrated funds perform better after controlling for risk and style differences. In a related paper, Cremers and Petajisto (2007) propose a measure of Active Share for individual mutual funds to capture the share of portfolio holdings that differ from the benchmark index. They find that funds with the highest Active Share values significantly outperform their benchmark, both before and after expenses. This paper, on the other hand, focuses on the universe of hedge funds and investigates whether innovative and distinctive strategies of hedge funds predict superior future performance.

This paper is also related to a burgeoning line of research that aims to gauge the unobserved fund managers’ talents using publicly observable fund return and holding data. Cohen, Coval and Pastor (2005) propose to judge a fund manager's skill by how similar her portfolio holdings are to those of managers with superior performance records. They demonstrate empirically that their measures are useful in forecasting manager performance. Kacperczyk, Sialm, and Zheng (2007) propose a return gap measure to capture the unobserved actions taken by mutual fund managers.

The return gap is defined as the difference between the reported fund returns and the return of a portfolio that invests in the previously disclosed holding adjusted for expenses. They find that the return gap, as a proxy for the unobserved managerial talents, indeed helps predict future fund performance. Kacperczyk and Seru (2007) argue that a skilled manager tends to rely less on public information. They construct a *RPI* measure (Reliance on Public Information) to capture the responsiveness of a mutual fund manager's portfolio allocations to changes in public information, and find a strong inverse relation between *RPI* and future fund performance. In this paper, we try to estimate the innovativeness of a fund's strategy, an unstudied aspect of disclosed fund performance, by analyzing fund historical returns.

III. Data

The hedge fund data are from the Lipper TASS database, which is recognized as one of the leading sources of hedge fund information. The main data include monthly hedge fund returns, as well as fund characteristics. We start with a total of 12784 funds, including live and graveyard funds. Then, following Aragon (2007), we filter out non-monthly filing funds and funds denoted in a currency other than US dollars. This leaves 8320 unique funds. To control for back fill bias, we further throw out the first 18 month returns for each fund, yielding 7250 unique funds.[1] We then filter out fund of funds (FOF), which reduces our sample to 5595 funds.[2] We also filter out observations before 1994 and after 2008, which leaves 5501 unique funds. To reduce the noise in

[1] We also consider an alternative approach to controlling for backfill bias by removing returns before a fund joins the TASS database, following Aggarwal and Jorion (2009). The resulting sample size and overall pattern of the main findings remain qualitatively similar.

[2] Our *SDI* measure may not work well to predict future performance for FoFs. First, overlapped holdings of the underlying hedge funds may reduce the spread in *SDI* across FoFs, which is confirmed in our unreported analysis, available upon request. Furthermore, superior FoFs may invest in similar underlying hedge funds, therefore there is a counteracting effect against finding a positive link between SDI and FoF performance. We thank an anonymous referee for this insight. In an unreported analysis, we find no significant association between *SDI* and FoF performance. The results are available upon request.

the fund distinctiveness measures, we exclude funds with less than 12 monthly returns within each preceding 24-month period, leading to a sample of 4602 unique funds. Moreover, we filter out funds with *AUM* less than 5 million dollars, giving 3630 remaining funds. Finally, for our regression analysis, we filter out funds with missing characteristics and extreme observations. This leaves a final sample of 3537 funds.

TASS groups these hedge funds into 10 self-reported style categories, including convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity hedge, managed futures, and multi strategies. A third of our sample funds are in the long/short equity hedge category. There are less than 30 funds in the dedicated short bias category. The rest of the sample is relatively evenly distributed over other 8 hedge fund categories.

The abnormal performance of a hedge fund is measured relative to certain benchmarks. Given the wide use of derivatives and dynamic trading strategies among hedge funds, the standard CAPM model cannot adequately capture the risk-return tradeoff for hedge funds. Therefore, we consider a few alternative choices as performance benchmarks. For our main results, we use the Fung and Hsieh (FH) 7-factor model (Fung and Hsieh 2001)[3], which includes an equity market factor, a size spread factor, a bond market factor, a credit spread factor, and trend-following factors for bond, currency and commodities.

In addition, we use a modified appraisal ratio of Treynor and Black (1973), which is calculated by dividing the mean of the monthly abnormal returns by their standard deviation. Brown, Goetzmann, and Ross (1995) show that survivorship bias is positively related to fund return variance. Thus, the higher the return volatility, the greater the difference between the ex-post

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[3] http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls

observed mean and the ex-ante expected return. Using the alpha scaled by the idiosyncratic risk as our performance measure mitigates such survivorship problems. Agarwal and Naik (2000) further point out that this measure is particularly relevant for hedge funds given that it accounts for differences in leverage across funds.

Moreover, we employ the Sharpe ratio to capture the risk-return tradeoff of hedge fund performance. It is defined as the ratio between the average monthly net fee returns in excess of the risk free rate and the volatility in the monthly excess returns. We also consider the smoothing-adjusted Sharpe ratio to control for illiquidity and smoothing in hedge fund returns, following Getmansky, Lo and Makarov (2004)[4]. Details of the adjustment are provided in Appendix A.

IV. Hedge Fund Strategy Distinctiveness Index

This paper investigates whether a more distinctive investment strategy reflects more innovative and skillful managerial talents, hence predicting superior future performance. To measure the distinctiveness of a fund's investment strategy, we compare its historical returns with the average returns of its peers.

A. Quantifying Hedge Fund Strategy Distinctiveness

If a manager is skillful, she is likely to engage in an innovative and unique trading strategy, thereby delivering performance that co-moves less with the overall performance of the hedge fund sector, or the performance of the specific style to which her fund belongs. This suggests an intuitive measure to capture the distinctiveness of a fund strategy: one minus the sample

[4] We thank an anonymous referee for this suggestion.

correlation of a fund's return (r_{it}) with the average return of all funds belonging to the same style (μ_{It}):

$$\begin{aligned} SDI_i &= 1 - corr(r_i, \mu_I) \\ &= 1 - \frac{\sum_{t=1}^{24}(r_{it} - \bar{r}_i)(\mu_{It} - \bar{\mu}_I)}{\sqrt{\sum_{t=1}^{24}(r_{it} - \bar{r}_i)^2 \sum_{t=1}^{24}(\mu_{It} - \bar{\mu}_I)^2}} \end{aligned} \quad (1)$$

where $\mu_{It} = \frac{\sum_{j \in I} r_{jt}}{count(j \in I)}$. The *SDI* ranges between 0 and 2 in theory. Graphically, *SDI* can be viewed as a "distance" measure: the higher the *SDI*, the farther a fund is from its cluster and the more distinctive is the fund's strategy.

To gauge how distinctive a fund's strategy is from its cohort, we first need to define hedge fund styles appropriately. Although TASS offers a classification scheme of 10 styles based on survey and voluntary reporting of hedge fund managers, this classification has a number of limitations.

First, the TASS style classification is based on voluntary self-reporting, which may be error-ridden and possibly subject to managerial manipulation. Despite the lack of direct evidence, we design a test shedding light on this issue. The premise of our test is that if the TASS classification is accurate, we would expect returns of a fund to have the highest R^2 (or correlation) with the self-reported TASS style index returns. For each hedge fund, we estimate the R^2 (or correlation) of returns associated with each of the 10 TASS style indices using the whole time series. The index yielding the highest R^2 (correlation) is identified as the "best fit index" for that fund. We then count the fraction of hedge funds whose "best fit index" coincides with its self-reported TASS style index. The more accurate the TASS style classification is, the higher the fraction is expected to be. Our results show that only 37% (40%) of funds turn out to have the self-reported

TASS style index as the “best fit index” based on R^2 (correlation). This evidence substantiates our concern of misspecification in the self-reported TASS styles.

Second, the TASS database only provides the last snapshot for fund style and characteristics Therefore, we are unable to examine if, and to what extent, hedge funds change styles over time. Ideally, if hedge fund holding and trading information were available, we could evaluate whether there is any style switching by hedge funds. Such information, however, is unavailable. Therefore, we design another test to examine the stability of the “best fit index” for each fund. Specifically, at each quarter for each fund, we use a rolling window of 24 months to estimate the R^2 (correlation) of individual fund returns with each of the 10 TASS styles. We identify the “best fit index” for that fund that yields the highest R^2 (correlation) at that quarter. If the “best fit index” for a fund changes over two consecutive quarters, we consider this as a style switch. We count the fraction of time a fund experiences style switching, then average across funds. We find that on average, 31% (27%) of time, a fund switches style over time. This evidence suggests that the latest snap shot of the TASS styles may not be the most accurate in capturing the true investment and trading style for individual funds over time.

Third, and perhaps most problematically, funds in broadly defined styles may appear more distinctive than those in other narrowly defined styles, not necessarily because of their distinctive strategy, but due to larger dispersion within the broadly defined style. In this case, the difference in *SDI* measure may reflect the style difference. In particular, we compare the distribution of *SDI* for each style and find large variations across TASS styles. For example, the average *SDI* for the Dedicated Short Bias is 0.27, while that for the Equity Market Neutral is 0.82. This suggests a possible confounding style effect associated with the TASS style based *SDI* measure.

To address these issues, this paper defines styles (i.e. cluster styles) by clustering historic returns. At the beginning of each quarter, for funds with more than 12 monthly returns over the preceding 24-month period, we group them into K clusters, i.e. K styles, based on the correlation of fund returns. The clustering procedure is similar to the method in Brown and Goetzmann (1997, 2003). The goal of the procedure is to find a locally optimized partition among funds so that it minimizes the sum of the distance of all funds to the corresponding clusters. This quantitative method, by design, groups each fund to its closest cohort and allows funds to switch styles over time as needed. It also balances among all clusters so that the strategy distinctiveness measure is more comparable across clusters. For example, the lowest average *SDI* for a cluster is 0.30, while the highest for a cluster is at 0.47. The difference of 0.17 is much smaller than the spread between 0.82, the average *SDI* for the equity Market Neutral, and 0.27, the average *SDI* for dedicated short bias. Therefore, the cluster style-based *SDI* is less likely subject to the confounding style effect than the TASS style-based *SDI*.

B. Properties of the Cluster Styles

To better understand the clustering results, first, we compare how much overlapping there is between the statistically defined cluster styles and the self-reported TASS styles. In our study, we fix the number of clusters to be ten, the same as the number of the TASS styles. In Table B1 in the appendix, we report the cross-tabulation of the cluster styles with the TASS styles. Since the self-reported styles are identified only at the end of the sample, we compare them with the end-of-sample clusters estimated based on the last 2 years return data[5]. As seen from Table B1, the cluster styles and the TASS styles do not perfectly match. Each of the relatively narrowly defined styles such as “Convertible Arbitrage”, “Dedicated Short Bias”, “Emerging Markets”, and “Managed Futures”, tends to concentrate in one or two clusters, which, combined, consist of over

[5] We also compare clusters defined based on the whole sample of returns with the TASS styles. The results are similar.

50% of funds in that style. This confirms that the clustering methodology indeed groups together funds with similar strategies. On the other hand, funds in broadly defined styles such as "Equity Market Neutral", "Event Driven", "Fixed-Income", "Global Macro", "Long-Short Equity" and "Multi-Strategy", spread widely across clusters. This further indicates that the TASS style classification may lump together funds that are fundamentally different, thus making it problematic to construct the strategy distinctiveness measure based on the TASS styles.

Second, we examine the stability of the clustering results. Since we update the clusters over time, funds belonging to one cluster this quarter may not necessarily be grouped together in the next quarter. However, if two funds are grouped together because of some fundamental link, then the clustering should remain stable over time. We test this hypothesis by analyzing pair-wise connections between funds for each period, and the details are provided in Appendix B2. Each year, we count the fraction of changes in the pair-wise connections between funds, which is considered as the "switching rate." We find an average annual switching rate of 16.2%, comparable to 17.6% found by Goetzmann and Brown (1997) based on a mutual fund sample. The low switching rate confirms the stable grouping by the clustering procedures. We also bootstrap the switching rate under the null hypothesis that funds are grouped into clusters by random chance. The average switching rate under the null is 29.7%. Plotting the entire distribution of the null rate reveals that the sample switching rate for each year is below the 1% percentile of the bootstrapped distribution, suggesting that the clusters are significantly more stable than if they were grouped by random chance.

C. Properties of the Strategy Distinctiveness Index (*SDI*)

In the following, we investigate the properties of the strategy distinctiveness index based on the cluster styles.

C.1. Heterogeneity of the Strategy Distinctiveness Index

There is a clear pattern of large variations in the distinctiveness of trading strategies across hedge funds. Panel A of Table 1 reports the time series averages of the cross-sectional summary statistics of the main variables. The Strategy Distinctiveness Index has a mean (median) of 0.32 (0.29), with a standard deviation of 0.18. The histogram presented in Figure 1A further confirms the heterogeneous pattern in *SDI*. Over 80% the sample funds exhibits an *SDI* of lower than 0.50. The distribution is over 15% in each of the 0.15 to 0.35 Index bins, and close to or over 10% in both the 0.05 and 0.45 Index bins. Funds scoring higher than 0.70 in *SDI* account for less than 5% of the total sample.

To see whether the clustering method better classifies funds than the self-reported TASS styles, we also compute the *SDI* based on the TASS styles. Specifically, we calculate one minus the sample correlation between each fund's returns with the average returns of all funds within the same TASS style. Figure 1B plots the histogram of *SDI* based on the TASS styles. As can be seen from the figure, the TASS style-based *SDI* is more right skewed compared with the cluster style-based *SDI*. The mean is 0.52, which is considerably higher than the average cluster style-based *SDI* of 0.32. Also note that there are 10% of funds with TASS style-based *SDI* higher than 1, indicating that the funds' returns are actually negatively correlated with the average returns of the funds within the same TASS styles. Overall, these patterns confirm that the clustering methodology better identifies funds with similar strategies.

A comparison of the cluster style-based *SDI* measure between the live and graveyard funds shows a similar level of *SDI*: the means of *SDI* for the live and graveyard funds are 0.31 and 0.33, respectively. Moreover, the proportion of the live and graveyard funds remains at about 40-60 split across the index bins, as evident in Figure 1A. These statistics suggest that findings on the relation between the *SDI* and fund performance are not likely driven by the different levels of *SDI* for live and graveyard funds.

In Figure 2, we examine the relative distribution of hedge funds across cluster styles in each of the index bins. The relative proportion of each cluster is stable across the bins. This finding suggests that the difference in the *SDI* measure is not driven by the difference in cluster styles, and hence any performance difference associated with the *SDI* is also unlikely driven by the style difference.

To better understand how *SDI* varies across funds with different characteristics, we report the time series average of the pair-wise correlations between the *SDI* and the contemporaneous fund characteristics. Panel B of Table 1 yields several noteworthy points. First of all, there is a positive correlation between *SDI* and fund performance as measured by alpha, appraisal ratio and Sharpe ratio. Second, there is a negative correlation between *SDI* and fund return volatility (*Vol*). Finally, younger funds with longer redemption notice period and with higher incentive fees tend to have higher *SDI* in our sample.

C.2 Persistence in the Strategy Distinctiveness Index

If the deviation in hedge fund returns from its peers is driven by innovations in trading strategies and managerial skills, funds should display persistent *SDI* over time. For example, if a hedge fund exhibits high *SDI* in one period due to the manager's unique informational advantage or the unique approach in processing information, its index level is likely to remain high in the future: managers are inclined to their usual resources and styles, as long as the market capacity for this type of strategy has not been fully exhausted.

To test this hypothesis formally, we sort all funds in our sample into quintile portfolios according to their lagged *SDI* measures and compute the average *SDI* for each quintile during the subsequent 3 months, 6 months and 1 to 3 years. Note that the *SDI* measure is always constructed using a rolling 2-year window. Also note that there is no look-ahead bias, as we keep a fund whenever it exists if it does within 3 years. Table 2 reports the average index levels of the quintile portfolios both at the sorting time and during the next 3 months to 3 years. The future index levels of the high Index portfolios remain higher than those of the low index portfolios, for all 5 holding horizons we considered. The difference in the *SDI* between the high and low index portfolio decreases over time, but remains economically and statistically highly significant even after 3 years, at a level of 0.20. These results suggest a strong persistence in the *SDI* measure.

D. Determinants of Strategy Distinctiveness Index

To better understand what affects the level of distinctiveness of a hedge fund performance, in this subsection, we examine the relation between the *SDI* and lagged fund-specific characteristics. Specially, we use a multivariate panel regression approach based on annual data, controlling for fund clustering and time and cluster style fixed effects. The lagged fund characteristics considered include fund return volatility (*Vol*), lengths of redemption notice and lock up periods, personal capital commitment dummy, high water mark dummy, management fees, incentive fees, fund age, natural logarithm of asset under management, flow into funds, minimum investment, leverage dummy, average monthly net fee returns, FH 7-factor alpha and the corresponding appraisal ratio (*AR*), and the Sharpe ratio (*SR*).

Table 3 summarizes the results, which are consistent with the overall patterns we observe from the correlation matrix in Panel B of Table 1. Specifically, *SDI* increases with both the average net fee returns and the risk adjusted performance measures including the FH7 alpha, *AR* and *SR*, indicating a positive relation between *SDI* and fund performance. This finding is consistent with the skill effect. Moreover, *SDI* decreases with *Vol*, length of lockup period, high water mark dummy, fund age and fund size, while it increases with the length of redemption notice period, personal capital dummy, fund incentive fees, past fund flows, minimum investment and use of leverage. The negative relation between *SDI* and *Vol* suggests that our measure of fund performance deviation from its peers is unlikely driven by managers making random bets and taking on excessive risk to maximize the option-like payoff. Instead, the deviation measured by our index is likely associated with managerial talents in designing and implementing innovative strategies. The statistically significant association of *SDI* with the redemption notice period and high water mark dummy makes economic sense. A longer redemption notice period gives managers a better cushion to implement their investment ideas, therefore allowing for more room to be innovative. High water mark clauses, on the other hand, may make managers more risk averse, and hence, more likely to herd. The results regarding fund age, size, usage of personal capital and incentive fees are intuitive if *SDI* reflects innovation talents. Young funds are likely to have innovative ideas. Small funds, being more nimble, can more readily incorporate innovations into their current practice. Commitment of personal capital and higher incentive fees may better motivate managers to pursue innovative and profitable strategies. It's also consistent that more talented managers may charge higher fees, or that they are more willing to invest their own money there.

V. Strategy Distinctiveness Index and Fund Performance

Until now, we have provided evidence that *SDI* has appealing properties that are consistent with its potential of being an effective proxy for managerial innovation skills. In this section, we test the main hypothesis of the paper, i.e. whether *SDI* indeed contains valuable information that could be used to predict future fund performance. We probe this question using both a portfolio sorting and a multivariate predictive regression approach.

A. Portfolio Sorting

To gauge the relative performance of funds with different *SDI* levels, at the beginning of each quarter, we sorted all hedge funds into 5 portfolios according to their *SDI* levels measured over a previous 24-month period. For each quintile portfolio, we computed the equally and value weighted average buy-and-hold performance for the subsequent quarter. We also consider performance of these quintile portfolios held for the subsequent 6 months, and 1 to 3 years.

We consider various performance measures for each quintile portfolio including the average FH 7-factor adjusted alphas, a modified appraisal ratio of Treynor and Black (1973), and the smoothing-adjusted Sharpe ratio. For each fund, we compute the monthly FH 7-factor alpha using a rolling estimation of the prior 24 months. We then compound the monthly alpha to derive the 3-month and up to 3-year cumulative alpha for each fund, and then average across funds within each quintile to get the corresponding portfolio alphas. The appraisal ratio for each fund is calculated as the ratio between the mean of its monthly FH 7-factor adjusted returns over the holding period and the standard deviation of the monthly alphas. The Sharpe ratio is calculated in a similar way using the monthly net fee returns in excess of the risk free rate and adjusted for smoothing as detailed in Appendix A. We then took the average within each portfolio to derive the appraisal ratio and Sharpe ratio of the quintile portfolios. Table 4 summarizes the time-series average of these performance measures for each quintile portfolio, as well as the difference between the high and low *SDI* portfolios. The corresponding t-statistics are adjusted for heteroskedasticity and auto-correlation.

For the equally weighted portfolios, the FH 7-factor alphas increase almost monotonically with the past *SDI* measures for all five holding horizons. For a trading strategy of sorting every 3 months and holding for the subsequent year, funds in the highest *SDI* quintile, where managers tend to follow distinctive investment strategies, earn an abnormal return of 7.95% per annum, with a t-statistics of 8.59. Those in the lowest *SDI* quintile, where managers tend to herd the most, on the other hand, yield a return of 4.00% each year after controlling for FH 7-factor. The performance difference between the top and bottom quintiles is 3.95% per annum and statistically significant. For other holding horizons, funds in the highest *SDI* quintile consistently outperform those in the lowest quintile by about 2-4% per annum after adjusting for FH 7-factor. Note, to earn these return spreads, one has to set up a trading strategy going long on funds with the most innovative investment skills and short on those most likely to herd. The long-side of this trading strategy alone can actually secure a better abnormal return of 6-8% per annum for all holding horizons.

As a fund deviates from its benchmark performance, it will be exposed to idiosyncratic risk. To take into account the different levels of unique risk across our sample of funds, we use a modified appraisal ratio of Treynor and Black (1973). For the equally weighted portfolios, there is a clear tendency for the appraisal ratio to increase with the *SDI*. The difference between the top and bottom *SDI* portfolios is 0.35 with a t-statistic of 4.11 for a holding horizon of 3 months. When the holding horizon is extended to a 1-year period, the difference in appraisal ratio between the high and low *SDI* portfolios converges, but still remains highly significant at a level of 0.26 with a t-statistic of 5.57. The difference in appraisal ratio shrinks to 0.20 and remains significant when the holding horizon is extended to 3 years.

To ensure that our portfolio sorting results are not specific to the FH 7-factor performance benchmark, we also consider the smoothing-adjusted Sharpe ratio that is based on the monthly net fee returns in excess of risk free rate[6]. The equally weighted portfolio Sharpe ratio increases monotonically from the lowest *SDI* quintile to the highest one for all 5 sorting and holding

[6] Results based on the raw Sharpe ratios yield similar findings, and are available upon request.

horizons. For the 1-year holding horizon, the high *SDI* portfolio outperforms the low one by 0.12, significant at the 1% level. In general, the spread in the smoothing-adjusted Sharpe ratio ranges from 0.07 to 0.22 across various holding horizons, and is significant at the 1% level or better.

The value weighted portfolio sorting results are qualitatively similar compared to the equally weighted ones. For example, based on a 1-year holding period, funds in the highest *SDI* quintile significantly outperform those in the lowest quintile by 3.19% per annum, after controlling for the FH 7-factors. In general, the magnitude of the spread in the annualized FH 7-factor alpha between the value weighted extreme quintiles is smaller to that of the equally weighted portfolios, but still remains highly significant except for the case of 3-month holding horizon. The results using appraisal ratios and Sharpe ratios are essentially the same as the equally weighted ones, both in magnitude and statistical significance. Overall, these findings suggest that our results are not driven by small funds playing a dominant role.

B. Multivariate Predictive Regression Analysis

In this section, we further extend our analysis using a multivariate regression approach. The quintile portfolio analysis does not control for hedge fund characteristics that are known to affect future performance. For example, funds with more innovative investment strategies may be smaller than those likely to herd. Moreover, managers of innovative funds may be offered different incentive contracts from those go-with-the-crowd managers. Our previous findings on a positive association between *SDI* and future fund performance may be driven by size or other fund characteristics. A multivariate regression framework can help differentiate the alternative explanations by simultaneously controlling for these different factors.

To investigate whether *SDI* has a predictive power for future fund performance after controlling for other fund-specific characteristics, we estimate the following:

$$AbnormalPerformance_{i,t} = c + SDI_{i,t-1} + Control_{i,t-1} + e_{i,t} \quad (2)$$

where $AbnormalPerformance_{i,t}$ are the risk adjusted fund performance within one year after the *SDI* is calculated. Specifically, we consider the compounded alpha, the corresponding appraisal ratio (*AR*), and the smoothing-adjusted Sharpe ratio (*SR*).

We use the lagged control variables to mitigate potential endogeneity problems. The $Controls_{i,t-1}$ consist of performance volatility measured by the volatility of past 24-month fund returns in percent (*Vol*), redemption notice period measured in unit of 30 days, lockup months, indicator variables for whether personal capital is committed and whether there is a high water mark requirement, management fees, incentive fees, ages of funds in years, natural logarithm of asset under management, flows into funds within the last year as a fraction of *AUM* in percent[7], average monthly net fee returns in the preceding 24-month period, minimum investment, and a dummy variable for use of leverage or not. These variables are suggested by the existing literature on hedge fund characteristics and performance. If the distinctiveness index indeed reflects innovative and skillful managerial talents, we should expect its estimated coefficient to be significantly positive.

Our data is a pooled time series and cross-sectional unbalanced panel data. Given the stale price issue for hedge fund data documented by Getmansky, Lo and Makarov (2004), the resulting alphas may be correlated over time for a specific fund, hence we must correct for the fund clustering effect. Moreover, hedge fund performance may also be correlated across funds at a given point of time. Therefore, we need to correct for the time effect. As Petersen (2005) shows, clustering standard error is the preferred approach in addressing the fund-effect, while Fama-MacBeth is appropriate for correcting for the time effect. When both effects exist, we need to

[7] To control for data errors, we excluded observations of flow higher than 1000% or lower than -1000%.

address one parametrically and then estimate standard errors clustered on the other dimension. We thus adopt two approaches. The first approach is the pooled panel regression adjusting for both fund clustering and time and style fixed effects. The second approach is the Fama-MacBeth cross-sectional analysis with style dummies and Newey-West heteroscedasticity and autocorrelation adjustment (HAC). Since there are only 12 years in our sample, the annual regression, especially for the Fama-MacBeth analysis, will be subject to the issue of limited statistical power. Therefore, our regressions use data of quarterly frequency.

B.1 Panel Regression Analysis

For the panel regression, we pooled the time series of all funds together to estimate Equation (2). The results are reported in Table 5, where the t-statistics are adjusted for fund-level clustering effect and time and cluster style fixed effects. Since risk adjusted returns better reflects managerial talents, we focus on the regression results with the FH 7-factor adjusted returns and the corresponding appraisal ratios, as well as the smoothing-adjusted Sharpe ratios, as the dependent variables. Table 5 demonstrates that the *SDI* has an important impact on future fund abnormal performance, even after controlling for other fund characteristics.

For the panel regression of alphas, the estimated coefficient for the *SDI* is 4.81 with a t-statistic of 4.10, when time and cluster style fixed effects are controlled. This implies that a one standard deviation increase in the *SDI* Index predicts an increase in the annualized FH 7-factor returns of 0.87 percent in the subsequent year, in the presence of a host of control variables. The signs of the coefficients for other fund characteristics are largely consistent with the existing literature. For example, the length of redemption notice period and lockup period is significantly and positively associated with future fund alpha. This corroborates with the findings in Aragon (2007) and Liang and Park (2008) which documents that funds with more stringent share restriction clauses offer higher returns to compensate for illiquidity. High water mark dummy variable and management fees are significantly and positively related to future alpha. These results are similar to the findings in Agarwal, Daniel, and Naik (2007) which argues that hedge funds outperform when managers are better incentivized. *AUM* is negatively associated with the future alpha, consistent with the notion of performance erosion due to increased scale in the mutual fund sector as discussed in Berk and Green (2004) and Chen, Hong, Huang, and Kubik (2004). Finally, FH 7-factor alpha increases with the minimum requirement for investment and the usage of leverage.

The FH 7-factors cover a large span of major asset classes, allowing the model to capture the risk-return tradeoff for hedge funds with different strategies. Hence, we have chosen the FH 7-factor model as the primary benchmark to gauge abnormal returns of hedge funds thus far. However, there are alternative performance benchmarks that contain relevant factors to capture the risk-return tradeoff for hedge funds. Following Agarwal and Naik (2004), we consider as alternative performance benchmarks a model combining Carhart 4 factors and returns on the at-the-money and the out-of-the-money call and put options on S&P 500. The panel regression yields a similar effect of the *SDI* on the new alpha. For example, a one standard deviation increase in the *SDI* leads to an increase of 0.97% in the new alpha in the subsequent year.

We also adopt the appraisal ratio as an alternative performance measure. The results indicate a strong positive association of the *SDI* and future appraisal ratio[8]. For example, a one standard deviation increase in the *SDI* will result in an increase in both the FH7-factor and AN8-factor appraisal ratios of 0.06 when time and cluster style fixed effects are controlled for. Finally, the effect of the *SDI* on the smoothing adjusted Sharpe ratio is also strongly positive and significant.

[8] We exclude lagged volatility from the regressor set for the appraisal ratio and the smoothing adjusted Sharpe ratio. Since both ratios are already scaled by volatility of alphas or excess returns, further regressing these variables on another return volatility measure may cause a mechanic negative link between them. Nevertheless, our main results on the positive association between SDI and performance measures remain the same regardless of the regression specification.

A one standard deviation increase in the *SDI* leads to an increase of 0.02 for the smoothing adjusted SR.

B.2 Fama-MacBeth Analysis

Using the Fama-MacBeth approach, each quarter, we performed the cross-sectional regression of Equation (2) together with cluster style dummies to get the estimated coefficients. Then, we used the time series of the estimated coefficients to derive the final Fama-MacBeth regression results with Newey-West heteroscedasticity and autocorrelation adjustment on standard errors. The results are reported in Table 6. For the regression of the FH 7-factor alphas, the estimated coefficient on the *SDI* is 4.45 with a t-statistics of 2.92, when cluster style dummies are controlled for. Since the difference in the *SDI* between the high and low portfolios up to 1-year post-formation falls between 0.31 and 0.51 according to Table 2, the implied difference in the FH 7-factor alpha between the extreme quintiles is about $0.31 \times 4.45 = 1.38\%$ to $0.51 \times 4.45 = 2.27\%$. Similarly, the difference in the FH 7-factor *AR* between the extreme quintiles is about $0.31 \times 0.35 = 0.11$ to $0.51 \times 0.35 = 0.18$. The implied difference in the smoothing-adjusted *SR* between the extreme quintiles is $0.31 \times 0.14 = 0.04$ to $0.51 \times 0.14 = 0.07$. Overall, the results from the Fama-MacBeth analysis are consistent with those from the panel regression and the portfolio analysis.

C. Robustness

In this section, we conduct robustness tests on our main findings. First, we investigate whether our results are robust to alternative specifications for strategy distinctiveness. Second, we examine whether our results hold up to a drop-out bias, which results from the fact that no performance is available after funds stop reporting to the TASS database.

C.1 Alternative *SDI* Measures

Despite the caveats associated with the TASS style classification detailed in Section IV.A, to ensure that our main findings are not specific to the cluster style classification, we conduct the portfolio sorting and multivariate regression analysis based on (1-correlation) using the TASS styles, termed as *SDI*(TASS). Results reported in Table 7 corroborate our main findings. In particular, the difference in the annualized FH 7-factor alpha between the equally weighted high and low TASS style based *SDI* quintiles ranges from 3.51% to 1.58% for a 3-month to 3-year holding horizon; the difference in the FH 7-factor based appraisal ratio ranges from 0.42 to 0.18; and the difference in the smoothing-adjusted Sharpe ratio ranges from 0.21 to 0.08, for a 3-month to 3-year holding horizon. These findings are consistent with the results based on cluster styles. Similar patterns are observed using the value-weighted portfolios. However, in the panel and Fama-MacBeth regression analysis, while *SDI*(TASS) continues to predict future alpha and appraisal ratio, its predictive power for the Sharpe ratio is not as robust as the cluster based *SDI* measure. The weakened results is likely due to the confounding style effect associated with *SDI*(TASS), which prompted us to focus on cluster style based *SDI* at the first place.

We also investigate whether another intuitive measure for the distinctiveness of a fund strategy is associated with future outperformance. In particular, we consider the R-squared of a regression of individual hedge fund returns against the average returns of all peer funds:

$$r_{i,t} = c_{0i} + c_{1i} Benchmark_t + u_{i,t} \qquad (3)$$

(1 – R^2) captures the percentage of total variance in fund returns that cannot be explained by the returns of all peer funds. The higher the (1-R^2), the more distinctive is the fund's strategy. For simplicity, we use TASS style as the benchmark. We then relate the 1-R^2(TASS) with the subsequent performance measures. The overall pattern in the results, reported in Table 7, again confirms that the more distinctive the strategy, the better future performance.

C.2 Control for Drop-out Bias

Although we include both live and graveyard funds in the portfolio analysis, there is no return data available after funds stop reporting and drop out of the data set. If the "drop out" funds continue to operate and the unreported performance of these funds is substantially different from the performance of existing funds, the observed portfolio return based on existing funds would be biased. We refer to this potential bias as the "drop out" bias. This bias raises the concern that the observed performance difference across the *SDI* quintiles might be due to the difference in the drop out rate rather than true performance. Fund and Hsieh (2000) point out that the magnitude of the "drop out" bias should be a fraction of the normal survivorship bias. To further examine this issue, we analyze the "drop out" property of the *SDI* portfolios and gauge the impact of the potential bias on our findings through some back of the envelop calculations.

Table 8 reports the survival rate for the *SDI* sorted portfolios corresponding to the ones reported in Table 2. In general, funds in the high *SDI* portfolios experience a higher drop out rate than funds in the low *SDI* portfolios. For example, about 84% of the funds in the lowest *SDI* quintile remain in the data set one year after portfolio formation, while 80% of the funds in the highest *SDI* quintile remain.

To examine whether the 4% difference in the drop out rate between extreme quintiles explains away the observed performance difference across the *SDI* quintiles, we need to know the performance of the funds after they drop out. Unfortunately, such data is not readily available. Funds drop out of the database for many reasons, such as liquidations, mergers, name changes, or voluntarily stopping reporting. As a result, even the sign of the bias is not clear. We assess the potential impact of drop-out bias through the following back of the envelope calculations. For each portfolio, the true risk adjusted return can be denoted as:

$$alpha^{True} = w^{Surviving} alpha^{Surviving} + w^{Dropout} alpha^{Dropout}.$$

The difference in the true performance between the high and low *SDI* portfolios is then given by:

$$alpha_{Hi}^{True} - alpha_{Low}^{True} =$$
$$w_{Hi}^{surviving} alpha_{Hi}^{Surviving} + w_{Hi}^{Dropout} alpha_{Hi}^{Dropout} - w_{Low}^{surviving} alpha_{Low}^{Surviving} - w_{Low}^{Dropout} alpha_{Low}^{Dropout}$$

Since there is no direct way to measure the performance of funds after they leave the database, assuming $alpha_{Low}^{Dropout} = alpha_{Hi}^{Dropout} = alpha^{Dropout}$, we will explore at what level $alpha^{Dropout}$ would wipe out the difference in the true performance between the high and low *SDI* portfolios.

Take the equally weighted 1 year post-formation case as an example. Based on Table 4A and Table 8, $alpha_{Hi}^{True} - alpha_{Low}^{True} = 0.80 \times 7.95\% - 0.84 \times 4.00\% + (0.20 - 0.16) alpha^{Dropout}$. As long as the annualized $alpha^{Dropout} \geq -75\%$ for funds one year after dropping out, the true performance of the high *SDI* portfolio beats that of the low *SDI* one.

VI. Conclusion

Investors want to identify talented hedge fund managers who have unique alpha generating investment ideas. Since little information about the funds' security holdings or trading strategies is disclosed to investors, assessing managerial ability is a challenging task that relies mainly on learning from funds' historical return information and managers' track records. Academic literature has studied how past fund performance relates to future fund performance. In this paper, we examine a different aspect of fund historical returns, namely the extent to which a fund's return series resembles the return series of its peer funds. We hypothesize that skilled managers with innovative ideas would herd less, and thus their returns would display less resemblance to those of an average fund.

To measure the distinctiveness of a fund's investment strategy, we estimate the correlation of a fund's returns with the average returns of its peer funds. We term (1 – correlation) the "Strategy Distinctiveness Index" (*SDI*). Using fund return data from January of 1994 to December of 2008, we document a substantial cross-sectional variation in the *SDI*, indicating much heterogeneity in funds' style distinctiveness. We also find strong persistence in the individual funds' *SDI* for years into the future, which suggests that the *SDI* reflects persistent fund specific factors. Further analysis indicates that *SDI* is related to a number of fund characteristics, for example, past fund performance, return volatility, fund age, size, the lengths of redemption notice period and lockup period, incentive fees, minimum investment and leverage usage.

Our main result shows that *SDI* is associated with significantly better future fund performance. Funds with high *SDI* tend to perform consistently better after adjusting for differences in their risks and styles. We show this finding using a portfolio approach, a panel regression approach and the Fama-MacBeth method. Overall, our evidence indicates that *SDI* is a potentially useful indicator of managerial innovative talents and can be used by investors in selecting funds.

Appendix A: Smoothing-adjusted Sharpe ratio

We use the smoothing-adjusted Sharpe ratio as opposed to the regular Sharpe ratio. Lo (2002) points out that hedge fund returns are subject to high serial correlations, which can bias the annualized Sharpe Ratio measured using monthly returns if autocorrelation in returns is not taken into account. Moreover, Getmansky, Lo and Makarov (hence GLM, 2004) show that due to illiquidity and smoothing, the unobserved true economic returns are different from the observed smoothed returns. Therefore, even the monthly Sharpe ratio itself that is based on the observed returns will be biased. GLM (2004) further propose an econometric model of return smoothing as well as an estimator for the smoothing-adjusted Sharpe ratio. In particular, the true return of a hedge fund R_t is determined by a linear factor model, as described below:

$$R_t = \mu + \beta\Lambda_t + \varepsilon_t, \quad \varepsilon_t, \Lambda_t \sim IID \quad \text{(A1)}$$

The true return R_t is not observable, instead we observed the smoothed returns R_t^o as follows:

$$\begin{array}{l} R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \ldots + \theta_k R_{t-k} \\ \theta_j \in [0,1],\ j = 0,\ldots,k \quad \text{and}\ \theta_0 + \theta_1 + \ldots\theta_k = 1 \end{array} \quad \text{(A2)}$$

The paper shows that the Sharpe ratio of the true unobserved return can be obtained by multiplying the regular Sharpe ratio based on the smoothed return by $\sqrt{\theta_0^2 + \theta_1^2 + \ldots + \theta_k^2}$. The coefficients ($\theta_0, \theta_{1,} \ldots\theta_k$) in equation (A2) can be estimated by maximum likelihood method. We assume that the observed returns depend on lagged true returns up to time (t-2). Thus the smoothing-adjusted Sharpe ratio is

$$SR = \sqrt{\theta_0^2 + \theta_1^2 + \theta_2^2}\, SR^o$$

Where SR^o is the regular Sharpe ratio calculated using observed monthly hedge fund returns.

Appendix B1: Comparing the TASS and Cluster Styles

Table B1: Cross-Tabulation of Self Reported TASS Styles and Cluster Styles (200701-200812)

Table B1 reports the cross-tabulation of cluster styles with the styles reported by hedge funds in TASS. The TASS styles are those attributed to the funds as of December, 2008. The clusters are obtained based on hedge fund returns from January 2007 to December 2008.

TASS Style\Cluster Style	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Row Total**
Convertible Arbitrage	0	17	2	11	1	34	12	6	2	9	94
Dedicated Short Bias	0	0	18	0	0	0	0	0	1	0	19
Emerging Market	0	3	3	6	72	35	72	14	4	9	218
Equity Market Neutral	11	16	18	15	30	29	14	24	8	4	169
Event driven	4	28	10	93	43	35	10	38	13	30	304
Fixed Income	9	22	13	13	6	34	16	6	3	22	144
Global Macro	8	9	16	14	19	15	23	10	30	6	150
Long Short Equity	38	61	37	219	267	45	162	113	43	69	1054
Managed Future	15	15	26	7	5	9	4	6	138	3	228
Multi Strategy	7	29	13	22	89	38	27	38	30	23	316
Column Total	92	200	156	400	532	274	340	255	272	175	2696

Appendix B2: Test of Clustering Stability

We study the stability of the clusters by looking at the pair-wise associations between funds in our sample. Ideally, funds currently clustered together due to fundamental links will stay clustered together in the next period if their strategies stay stable. At each time point, we define "connection" to be either 1 or 0 depending on whether the two funds fall into the same cluster or not. We then count the percentage of pair-wise connections that remain unchanged for the next year. A higher percentage of unchanged pair-wise connections indicate a more stable clustering. Table B2 gives the clustering stability results. Column 2 counts the number of pair-wise connections that stay the same, and column 3 counts the total number of pair-wise connections for funds that are alive in both sets of clusters. Column 4 gives switching rate, which is the percentage of connections changed from the previous clustering results. The average annual switching rate is 16.2%. To gauge the stability of the clustering through time, for each year we bootstrap the switching rate under the null hypothesis of funds being grouped by random chance. The null is constructed by forming samples via random draws without replacement from actual fund returns. We follow Abraham, Goetzmann, and Wachter (1994) and Goetzmann and Wachter (1995) for the bootstrap procedure. For each round of the bootstrap procedure, we set the number of clusters and the total number of funds equal to those statistics from the real sample. Column 5 reports the average switching rate for each year. The typical rate of change under the null is 29.7%, which is considerably higher than the sample switching rate of 16.2%. Column 6 reports the standard deviation of the bootstrapped distribution. The switching rate is below the 1% critical value in the left tail of the bootstrapped distribution for each sample year. Therefore, we reject the null of random grouping. Overall, our clustering procedures based on historical returns capture the fundamental links across funds, and hence, the resulting clusters are stable over time.

Table B2: Switching Rate of Pair-Wise Connections Between Funds

Table B2 summaries the pattern of the switching rate of fund clustering results. In each period, we study the pair-wise connection between funds; connection takes the value of 1 or 0, depending on whether the two funds under study fall into the same cluster or not. We then count the percentage of pair-wise connections remaining unchanged the next period. The higher the percentage, the higher the stability of clustering. Column 2 counts the number of pair-wise connections that remain the same as the last period, and column 3 counts the total number of pair-wise connections for funds that exist in both periods. Column 4 is the sample switching rate, which computes the percentage of connections that changed since the last period. Column 5 reports the bootstrapped switching rate under the null of random grouping. The last column reports the standard deviation of the bootstrapped null distribution.

Year	Unchanged Pairs	Total # of Pairs	Sample Switching Rate	Null Switching Rate	Std. Dev. (Null Switching Rate)
1996	94889	111156	14.63%	29.37%	0.24%
1997	143159	167910	14.74%	29.90%	0.21%
1998	215418	258840	16.78%	29.75%	0.19%
1999	347701	403651	13.86%	29.94%	0.22%
2000	468646	570846	17.90%	29.39%	0.23%
2001	609122	708645	14.04%	29.49%	0.24%
2002	757753	899811	15.79%	29.74%	0.21%
2003	939498	1128753	16.77%	29.47%	0.21%
2004	1178813	1407003	16.22%	30.17%	0.22%
2005	1529207	1842240	16.99%	29.58%	0.23%
2006	1772203	2143485	17.32%	29.63%	0.22%
2007	2020425	2521135	19.86%	29.64%	0.21%
2008	2023149	2536878	20.25%	29.74%	0.18%
Mean			16.24%	29.67%	

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Figure 1: Histogram of Hedge Fund Strategy Distinctiveness Index

Figure 1A represents the histogram of *SDI* based on the cluster styles for all funds from 1996-2008. It also depicts a breakdown between the live and graveyard funds in the distribution. Figure 1B represents the histogram of *SDI* based on the TASS styles.

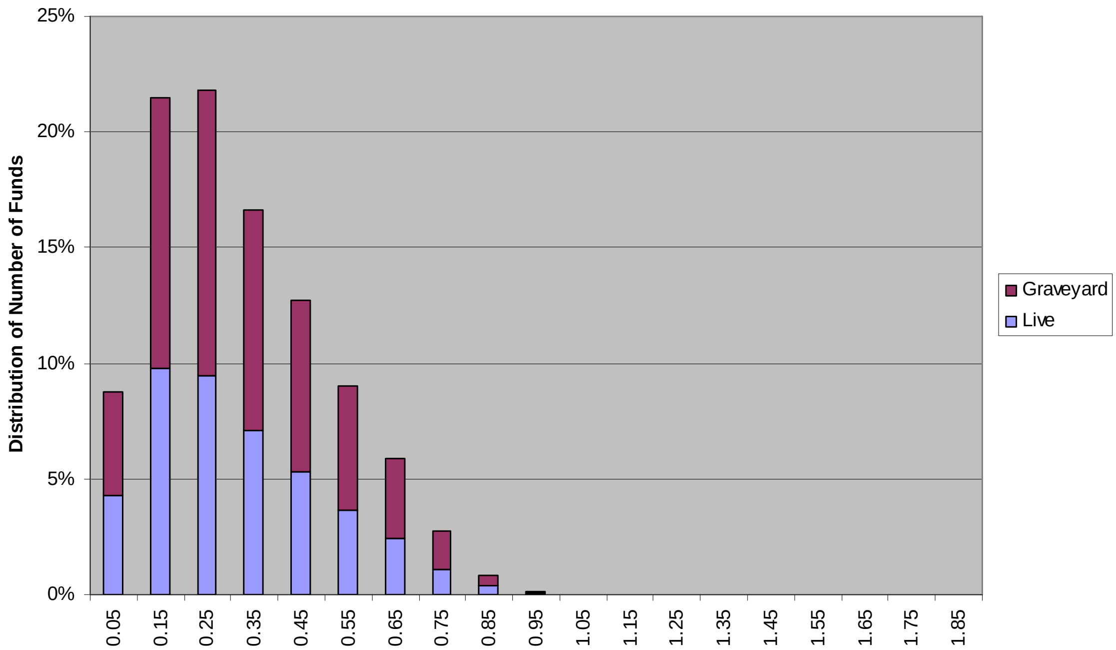

Figure 1A: SDI based on Cluster Styles

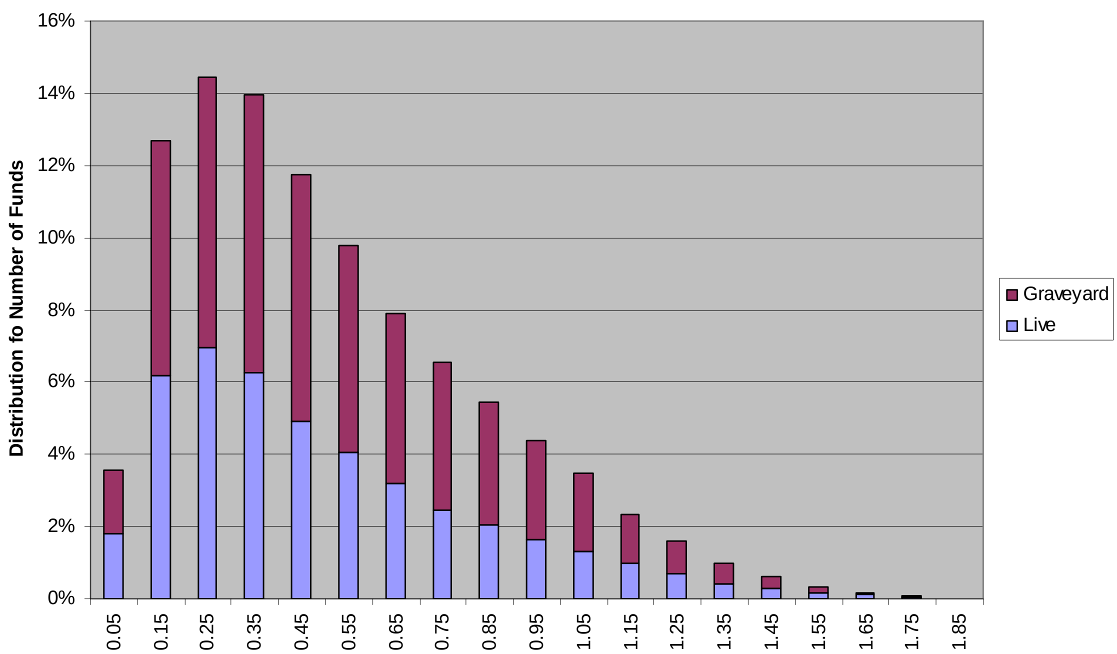

Figure 1B: SDI based on TASS Styles

Figure 2: Histogram of Hedge Fund Strategy Distinctiveness Index

Figure 2 represents the relative distribution of numbers of funds across the cluster styles for the *SDI* bins.

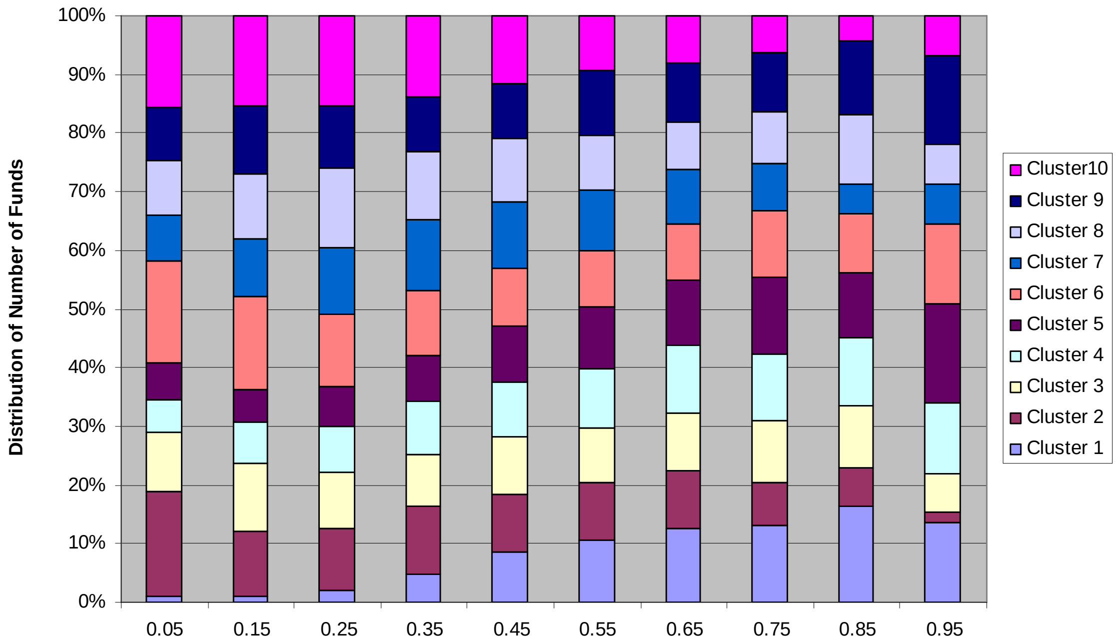

Figure 2: SDI Bins

Table 1: Summary Statistics (1996 - 2008)

Panel A summaries the time series averages of cross-sectional summary statistics for the main variables for the full sample, and for the live and graveyard fund sub-samples. Variables considered are number of funds per period, the Strategy Distinctiveness Index (*SDI*), measured as (1-correlation) from the clustering program, and contemporaneous fund characteristics including monthly net of fee returns, FH 7-factor adjusted alphas and the corresponding appraisal ratio (*AR*), Sharpe ratio (*SR*), volatility of monthly net fee returns (*Vol*), lengths of redemption notice periods and lockup periods, dummy variables for personal capital commitment and high water mark, management fees, incentive fees, fund age, assets under management (*AUM*), new money flow into funds within the past 12 months as a fraction of *AUM*, minimum investment, and dummy for leverage usage. Panel B reports the time series average of the pair-wise correlation between these variables.

Panel A: Fund Performance and Characteristics

	Full Sample (3792 unique funds)					Live Funds (1469 unique funds)					Graveyard Funds (2323 unique funds)				
	Mean	Median	Min	Max	Std	Mean	Median	Min	Max	Std	Mean	Median	Min	Max	Std
#Funds per period	1011	1024	291	1657	420	440	333	69	1348	346	571	615	130	822	188
SDI	0.32	0.29	0.00	0.90	0.18	0.31	0.28	0.00	0.85	0.18	0.33	0.29	0.00	0.89	0.18
NetFeeRet(% p.m.)	0.96	0.72	-24.87	64.88	5.34	1.15	0.86	-16.88	23.92	4.46	0.82	0.63	-22.10	62.25	5.54
Alpha(% p.m.)	0.75	0.69	-5.92	32.05	1.83	0.84	0.75	-3.67	8.51	1.32	0.69	0.65	-5.82	30.72	2.00
AR	0.53	0.39	-2.01	7.72	0.82	0.54	0.41	-1.38	5.51	0.76	0.53	0.39	-1.92	7.39	0.87
SR	0.23	0.13	-1.64	7.62	0.68	0.25	0.16	-1.22	5.26	0.66	0.22	0.11	-1.51	6.86	0.70
Vol(%p.m)	3.89	3.15	0.08	92.21	4.37	3.96	3.29	0.12	23.63	2.99	3.81	3.02	0.10	85.58	4.83
RedemptionNoticePeriod(days)	34.07	28.94	0.00	180.00	26.44	36.55	30.00	0.00	180.00	28.71	33.98	28.04	0.00	160.38	25.26
Lockup(months)	3.52	0.00	0.00	56.42	6.30	4.19	0.00	0.00	55.44	7.09	3.31	0.00	0.00	32.42	5.81
PersonalCapDummy	0.47	0.40	0.00	1.00	0.49	0.50	0.53	0.00	1.00	0.49	0.44	0.38	0.00	1.00	0.48
HighWaterMarkDummy	0.54	0.56	0.00	1.00	0.46	0.61	0.96	0.00	1.00	0.48	0.52	0.54	0.00	1.00	0.45
MgmtFee(%)	1.42	1.16	0.00	7.10	0.75	1.49	1.33	0.00	6.77	0.77	1.38	1.12	0.00	6.17	0.72
IncentiveFee(%)	18.13	20.00	0.00	49.36	5.89	18.95	20.00	0.00	34.84	4.52	17.80	20.00	0.00	49.23	6.37
Age(years)	6.54	5.55	2.50	32.06	3.71	6.97	5.90	2.51	25.21	4.03	6.25	5.33	2.50	31.66	3.46
AUM(M$)	190.22	57.85	5.00	6965.16	482.28	219.96	69.40	5.16	5314.59	513.20	176.63	51.92	5.03	6634.38	472.96
Flowpast1Y(%p.a.)	18.03	0.14	-161.48	819.06	82.55	22.09	3.38	-107.57	673.66	79.25	15.22	-1.47	-146.22	749.21	82.55
MinInvestment(M$)	0.97	0.56	0.00	35.58	1.87	1.13	0.53	0.00	31.92	2.31	0.92	0.65	0.00	21.83	1.50
Leverage	0.64	1.00	0.00	1.00	0.48	0.68	1.00	0.00	1.00	0.46	0.63	1.00	0.00	1.00	0.48

Panel B: Correlations

	SDI	NetFee Ret	Alpha	AR	SR	Vol	Redemp-tion NoticePeriod	Lockup	PersonalCap Dummy	HighWater Mark Dummy	Mgmt Fee	IncentiveFee	Age	AUM	MinInvestment	Leverage
NetFeeRet(% p.m.)	-0.01															
Alpha(% p.m.)	0.16	0.34														
AR	0.18	0.15	0.83													
SR	0.16	0.34	1.00	0.83												
Vol(%p.m)	-0.16	0.42	-0.24	-0.28	-0.24											
RedemptionNoticePeriod(days)	0.05	0.04	0.23	0.22	0.23	-0.15										
Lockup(months)	-0.02	0.07	0.07	0.05	0.07	0.00	0.31									
PersonalCapDummy	0.02	0.01	-0.02	-0.03	-0.02	0.03	0.03	-0.01								
HighWaterMarkDummy	0.01	0.05	0.10	0.09	0.10	-0.05	0.25	0.28	-0.10							
MgmtFee(%)	-0.02	0.06	-0.06	-0.06	-0.06	0.14	-0.20	-0.13	-0.08	-0.12						
IncentiveFee(%)	0.10	0.06	0.06	0.06	0.06	0.04	0.12	0.09	0.08	0.22	0.01					
Age(years)	-0.05	-0.03	-0.06	-0.06	-0.06	0.02	-0.08	-0.04	0.13	-0.18	0.04	-0.10				
AUM(M$)	-0.02	0.05	0.10	0.08	0.10	-0.05	0.08	0.04	0.03	0.01	0.01	-0.03	0.16			
Flowpast1Y(%p.a.)	0.04	0.11	0.11	0.07	0.11	-0.03	0.02	0.02	-0.02	0.05	0.01	0.02	-0.07	0.03		
MinInvestment(M$)	0.04	0.01	0.16	0.17	0.16	-0.12	0.17	0.12	0.04	0.17	-0.05	0.06	0.05	0.21	0.01	
Leverage	0.04	0.02	0.02	0.01	0.02	0.04	-0.05	-0.07	0.14	0.02	0.08	0.16	0.01	0.04	0.01	-0.02

Table 2: Persistence of the Strategy Distinctiveness Index (1996 - 2008)

Table 2 reports the time-series means of the average Strategy Distinctiveness Index (*SDI*) for the current quarter and the subsequent 3 months, 6 months, and 1 to 3 years for each of the quintile portfolios sorted on the previous 24-month *SDI*. It also reports the difference between the high and low portfolios and the corresponding t-statistics. Also reported are the time series mean of number of funds per period at the sorting and at the end of each holding horizon.

	Time 0	3m	6m	1y	2y	3y
SDI						
Low SDI Port	0.10	0.14	0.16	0.19	0.23	0.24
Port2	0.20	0.22	0.23	0.25	0.26	0.26
Port3	0.29	0.30	0.31	0.31	0.31	0.30
Port4	0.41	0.41	0.40	0.39	0.37	0.36
Hi SDI Port	0.61	0.56	0.54	0.50	0.45	0.44
Hi-Lo (SDI)	0.51	0.43	0.38	0.31	0.22	0.20
tstat	*121.51*	*68.19*	*47.23*	*29.32*	*19.23*	*24.17*
#Funds	1006	964	919	835	700	588

Table 3: Determinants of Strategy Distinctiveness Index (1996 - 2008)

Table 3 reports the estimates of the following panel regression of the Strategy Distinctiveness Index (*SDI*) on lagged fund characteristics using annual data: $SDI_{i,t} = c + Control_{i,t-1} + e_{i,t}$. Survivorship and backfill biases are controlled for to the extent the data allow. The *SDI* is measured as (1-correlation) from the clustering procedures. Lagged fund characteristics are measured over the preceding 24-month period including FH7 alpha and the corresponding appraisal ratio (*AR*), Sharpe ratio (*SR*), volatility of net fee returns (*Vol*), lengths of redemption notice periods and lockup periods, dummy variables for personal capital commitment and high water mark, management fees, incentive fees, fund age, assets under management (*AUM*), new money flow into funds as a fraction of *AUM*, minimum investment, dummy for leverage usage. The coefficients are multiplied by 100. The t-statistics reported in italics are adjusted for fund clustering effect and time and cluster style fixed effects.

	I	II	III	IV
VolPast2Y(%p.m.)	-0.48	-0.58	-0.12	-0.15
t-stat	*-2.00*	*-2.29*	*-0.46*	*-0.55*
RedemptionNoticePeriod(30 Days)	0.70	0.60	0.25	0.36
	1.88	*1.61*	*0.70*	*1.03*
Lockup(months)	-0.07	-0.08	-0.07	-0.07
	-1.71	*-1.78*	*-1.59*	*-1.62*
PersonalCapitalDummy	0.61	0.73	0.77	0.69
	1.05	*1.28*	*1.34*	*1.19*
HighWaterMarkDummy	-1.49	-1.43	-1.36	-1.37
	-2.18	*-2.10*	*-2.00*	*-2.01*
MgmtFee(%)	-0.07	-0.09	-0.07	-0.07
	-0.15	*-0.21*	*-0.17*	*-0.16*
Incentive Fee(%)	0.29	0.28	0.28	0.29
	5.13	*5.20*	*5.17*	*5.09*
Age(years)	-0.14	-0.12	-0.11	-0.14
	-2.08	*-1.76*	*-1.67*	*-2.00*
ln(AUM)	-1.01	-1.05	-1.09	-1.08
	-5.09	*-5.22*	*-5.66*	*-5.43*
FlowPast2Y in %	0.01	0.01	0.01	0.01
	3.38	*3.08*	*3.05*	*3.07*
ln(MinInvestment+1)	0.78	0.75	0.74	0.77
	3.60	*3.45*	*3.46*	*3.54*
Leverage	1.01	1.00	0.99	0.92
	1.76	*1.77*	*1.74*	*1.60*
AvgPast2YRet(% p.m.)	1.22			
	6.69			
AlphaPast2Y(%p.m)		1.57		
		9.16		
ARPast2Y			3.11	
			8.15	
SRpast2Y				4.70
				7.53
AdjR2(%)	10.64	11.65	11.69	11.44
#FundYearObs.	12911	12911	12874	12907

Table 4: Portfolio Performance Based on the Strategy Distinctiveness Index (1996 - 2008)

Table 4 reports the time series means and t-statistics of the post-formation FH7 alphas, FH7 based appraisal ratios (*AR*), and the smoothing adjusted Sharpe ratios (*SR*), for the quintile portfolios sorted on the Strategy Distinctiveness Index (*SDI*). The performance measures are based on the equally and value weighted buy-and-hold portfolios sorted every 3 months and held for 3 months, 6 months, and 1-3 years. The *SDI* is measured as (1-correlation), estimated using the clustering procedure. The t-statistics reported below in italics are adjusted for heteroskedasticity and auto-correlation.

	Alpha_FH7					AppraisalRatio					SharpeRatio(smoothing adjusted)				
	3m(%p.m.)	6m(%p.sa.)	1y(%p.a)	2y(%p.2y.)	3y(% p.3y.)	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
Panel A: Equally Weighted Portfolios															
LowSDIPort	1.03	1.70	4.00	8.66	13.81	0.23	0.16	0.15	0.14	0.12	0.21	0.14	0.13	0.11	0.10
tstat	*2.29*	*1.99*	*3.01*	*5.02*	*7.91*	*3.44*	*3.39*	*4.03*	*4.92*	*6.23*	*2.36*	*2.25*	*2.77*	*3.73*	*4.35*
Port2	1.43	2.61	5.29	11.08	17.68	0.31	0.23	0.21	0.18	0.17	0.29	0.19	0.16	0.14	0.13
tstat	*3.92*	*3.87*	*4.82*	*7.07*	*12.48*	*5.43*	*5.77*	*6.79*	*7.50*	*8.67*	*3.80*	*3.51*	*3.77*	*4.92*	*5.41*
Port3	1.78	3.35	7.14	14.95	21.66	0.41	0.30	0.27	0.25	0.22	0.31	0.22	0.18	0.17	0.15
tstat	*4.78*	*4.62*	*5.75*	*10.19*	*19.64*	*8.59*	*7.90*	*9.88*	*11.54*	*11.83*	*4.40*	*4.27*	*4.63*	*6.16*	*6.50*
Port4	1.89	3.87	7.49	15.14	22.16	0.51	0.40	0.33	0.29	0.26	0.36	0.26	0.21	0.18	0.16
tstat	*5.34*	*5.17*	*7.03*	*13.07*	*22.38*	*9.55*	*8.74*	*10.61*	*16.37*	*19.58*	*5.76*	*5.75*	*5.91*	*9.01*	*9.25*
HiSDIPort	1.92	3.82	7.95	15.14	21.82	0.58	0.47	0.41	0.35	0.32	0.43	0.31	0.25	0.20	0.17
tstat	*7.88*	*7.40*	*8.59*	*12.50*	*17.65*	*10.31*	*10.93*	*13.71*	*20.34*	*20.62*	*9.32*	*10.47*	*11.95*	*13.06*	*13.28*
Hi-Low	0.89	2.12	3.95	6.48	8.02	0.35	0.31	0.26	0.22	0.20	0.22	0.16	0.12	0.09	0.07
tstat	*2.17*	*3.09*	*3.80*	*5.88*	*5.22*	*4.11*	*5.20*	*5.57*	*7.71*	*8.99*	*3.01*	*3.46*	*3.48*	*3.68*	*3.98*
Annualized FH7 Alpha Hi-Low(%p.a.)	3.63	4.29	3.95	3.19	2.60										
Panel B: Value Weighted Portfolios															
LowSDIPort	1.00	1.57	3.86	8.46	14.54	0.29	0.22	0.22	0.21	0.20	0.26	0.19	0.18	0.15	0.14
tstat	*1.94*	*1.58*	*2.37*	*4.09*	*7.56*	*3.09*	*3.28*	*3.95*	*4.97*	*6.34*	*2.36*	*2.61*	*3.13*	*4.08*	*4.99*
Port2	1.55	2.60	4.55	9.22	15.48	0.44	0.33	0.27	0.25	0.24	0.40	0.27	0.21	0.20	0.19
tstat	*3.48*	*2.85*	*2.93*	*3.38*	*4.59*	*5.27*	*5.54*	*6.06*	*5.65*	*5.74*	*4.33*	*3.75*	*3.78*	*5.06*	*5.64*
Port3	1.76	3.57	7.93	16.00	22.42	0.52	0.39	0.34	0.31	0.28	0.36	0.26	0.23	0.21	0.18
tstat	*3.26*	*3.78*	*4.86*	*6.11*	*9.64*	*7.64*	*7.14*	*7.89*	*8.39*	*7.58*	*3.04*	*3.86*	*4.60*	*5.14*	*4.82*
Port4	1.70	3.47	5.96	13.44	19.58	0.59	0.45	0.38	0.36	0.32	0.36	0.29	0.23	0.23	0.20
tstat	*3.12*	*3.17*	*3.12*	*4.89*	*8.36*	*7.84*	*7.74*	*7.30*	*8.50*	*8.96*	*4.33*	*4.90*	*4.40*	*5.38*	*4.91*
HiSDIPort	1.38	2.82	7.05	14.03	20.02	0.73	0.61	0.56	0.50	0.44	0.53	0.38	0.32	0.25	0.22
tstat	*2.26*	*3.32*	*7.18*	*12.21*	*12.77*	*7.89*	*7.76*	*9.72*	*12.73*	*16.52*	*7.08*	*6.30*	*7.42*	*9.92*	*8.68*
Hi-Low	0.37	1.24	3.19	5.58	5.48	0.45	0.39	0.34	0.29	0.25	0.27	0.19	0.14	0.10	0.09
tstat	*0.60*	*1.34*	*2.39*	*4.31*	*3.80*	*3.35*	*3.82*	*4.14*	*5.77*	*7.49*	*2.33*	*2.58*	*2.41*	*2.35*	*2.46*
Annualized FH7 Alpha Hi-Low(%p.a.)	1.50	2.50	3.19	2.75	1.79										

Table 5: Panel Regression of Hedge Fund Performance on the Strategy Distinctiveness Index (1996Q1 - 2008Q4)

Table 5 reports the panel regression results for hedge fund performance on the Strategy Distinctiveness Index (*SDI*) and other fund characteristics at the quarterly frequency as the following: $\alpha_{i,t} = c + SDI_{i,t-1} + Control_{i,t-1} + e_{i,t}$. Survivorship and backfill biases are controlled for to the extent data allow. $\alpha_{i,t}$ is the compounded FH 7-factor adjusted performance over the subsequent 1 year in percentage terms. *AR* and *SR* are the corresponding appraisal ratio and Sharpe ratio. Control variables are the lagged fund characteristics including volatility of monthly net fee returns (*Vol*), lengths of redemption notice periods and lockup periods, dummy variables for personal capital commitment and high water mark, management fees, incentive fees, fund age, asset under management (*AUM*), new money flow into funds within the preceding 12 months as a fraction of *AUM*, in percentage, minimum investment, and dummy for leverage usage. The t-statistics reported underneath the estimated coefficients in italics are adjusted for fund clustering effect and time and cluster style fixed effects.

	Panel Regression		
	alpha(% p.a.)	AR	SRAdj.
	FH7	FH7	
SDI	4.81	0.33	0.13
tstat	*4.10*	*9.19*	*4.96*
VolPast2Y(%p.m)	0.08		
	0.50		
RedemptionNotice(30Days)	0.92	0.09	0.06
	3.17	*5.52*	*5.57*
Lockup(months)	0.08	0.00	0.00
	2.16	*-1.29*	*-0.88*
PersonalCapitalDummy	-0.30	-0.03	-0.01
	-0.69	*-2.03*	*-0.75*
HighWaterMarkDummy	0.99	0.01	0.01
	1.81	*0.47*	*0.92*
MgmtFee(%)	0.93	0.00	0.02
	2.62	*0.34*	*2.71*
IncentiveFee(%)	0.04	0.00	0.00
	0.87	*-1.78*	*-1.68*
Age(years)	0.00	0.00	0.00
	-0.06	*1.06*	*1.34*
ln(AUM)	-0.56	0.03	0.01
	-3.96	*5.71*	*4.15*
FlowPast1Y(%)	0.00	0.00	0.00
	-1.75	*1.24*	*0.57*
AvgPast2YRet(% p.m.)	0.14	-0.02	0.01
	0.44	*-3.81*	*2.74*
ln(MinInvestment+1)	0.73	0.03	0.02
	4.66	*5.53*	*4.98*
Leverage	0.03	0.00	0.01
	0.06	*0.16*	*1.32*
AdjR2(%)	5.22	10.72	14.85
#FundQtrObs	46997	46997	42106

Table 6: Fama-MacBeth Analysis of Hedge Fund Performance on the Strategy Distinctiveness Index (1996Q1 - 2008Q4)

Table 6 reports the Fama-MacBeth regression results for hedge fund performance on the Strategy Distinctiveness Index (*SDI*) and other fund characteristics at the quarterly frequency as the following: $\alpha_{i,t} = c + SDI_{i,t-1} + Control_{i,t-1} + e_{i,t}$. Survivorship and backfill biases are controlled for to the extent data allow. $\alpha_{i,t}$ is the compounded FH 7-factor adjusted performance over the subsequent 1 year in percentage terms. *AR* and *SR* are the corresponding appraisal ratio and Sharpe ratio. Control variables are the lagged fund characteristics including volatility of monthly net fee returns volatility, lengths of redemption periods and lockup periods, dummy variables for personal capital commitment and high water mark, management fees, incentive fees, fund age, asset under management (*AUM*), new money flow into funds within the preceding 12 months as a fraction of *AUM*, in percentage, minimum investment, and dummy for leverage usage. Cluster style dummies are included in the regressor set. The t-statistics reported underneath the estimated coefficients in italicized font are adjusted for heteroskedasticity and auto-correlation.

	Fama-MacBeth Regression		
	alpha(% p.a.)	AR	SRAdj
	FH7	FH7	
SDI	4.45	0.35	0.14
tstat	*2.92*	*5.11*	*3.26*
VolPast2Y(%p.m)	0.03		
	0.10		
RedemptionNotice(30Days)	0.80	0.07	0.05
	3.56	*11.35*	*7.13*
Lockup(months)	0.15	0.00	0.00
	2.54	*-0.88*	*-0.45*
PersonalCapitalDummy	-0.30	-0.03	-0.02
	-0.61	*-2.91*	*-1.40*
HighWaterMarkDummy	0.85	0.03	0.02
	0.93	*1.40*	*1.63*
MgmtFee(%)	1.08	0.00	0.02
	2.36	*-0.05*	*2.47*
IncentiveFee(%)	0.01	0.00	0.00
	0.38	*-1.76*	*-1.71*
Age(years)	-0.04	0.00	0.00
	-0.71	*0.06*	*0.03*
ln(AUM)	-0.58	0.03	0.01
	-2.29	*4.59*	*3.17*
FlowPast1Y(%)	0.00	0.00	0.00
	-1.55	*2.55*	*1.13*
AvgPast2YRet(% p.m.)	0.61	-0.02	0.02
	0.86	*-0.98*	*2.49*
ln(MinInvestment+1)	0.79	0.03	0.02
	3.24	*5.25*	*7.34*
Leverage	0.38	0.00	0.02
	0.93	*-0.17*	*1.79*
AdjR2(%)	18.11	17.70	14.73

Table 7: Robustness: Alternative *SDI* Measures (1996Q1 - 2008Q4)

Panel A of Table 7 reports the portfolio sorting results using alternative measures of *SDI* including (1-correlation) based on the TASS styles, and 1-R^2 based on TASS styles. Quintile portfolios are created by sorting on various *SDI*s every 3 months and held for 3 months, 6 months, and 1-3 years. The performance measures are based on the equally and value weighted buy-and-hold portfolios. Reported are the time series means and t-statistics of the post-formation FH7 alphas, FH7 based appraisal ratios (*AR*), and the smoothing adjusted Sharpe ratios (*SR*) between the highest and the lowest *SDI* portfolios. The t-statistics reported below in italics are adjusted for heteroskedasticity and auto-correlation.

Panel B reports the panel regression and Fama-MacBeth regression results for hedge fund performance on alternative *SDIs* and other fund characteristics at the quarterly frequency as the following: $AbnormalPerformance_{i,t} = c + SDI_{i,t-1} + Control_{i,t-1} + e_{i,t}$. Survivorship and backfill biases are controlled for to the extent data allow. $\alpha_{i,t}$ is the compounded FH 7-factor adjusted performance over the subsequent 1 year in percentage terms. *AR* and *SR* are the corresponding appraisal ratio and smoothing adjusted Sharpe ratio. Control variables are the lagged fund characteristics including volatility of monthly net fee returns (*Vol*), lengths of redemption notice periods and lockup periods, dummy variables for personal capital commitment and high water mark, management fees, incentive fees, fund age, asset under management (*AUM*), new money flow into funds within the preceding 12 months as a fraction of *AUM*, in percentage, minimum investment, and dummy for leverage usage. Panel regression is adjusted for fund clustering effect and time and cluster style fixed effects, and Fama-MacBeth regression controls for cluster style dummies and adjusts for heteroskedasticity and auto-correlation in standard errors. For brevity, only the estimation results for the *SDI* are reported here.

Panel A: Portfolio Sorting

	Annualized FH7 Alpha(%p.a.)					AppraisalRatio					SharpeRatio(smoothing adjusted)			
	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y	3m	6m	1y	2y
SDI(TASS)														
Hi-Low(EW)	3.51	3.35	3.42	2.25	1.58	0.42	0.31	0.26	0.21	0.18	0.21	0.16	0.13	0.09
tstat	*2.34*	*2.02*	*2.73*	*3.69*	*2.51*	*6.08*	*6.04*	*5.57*	*12.41*	*10.54*	*3.02*	*3.21*	*3.05*	*2.58*
Hi-Low(VW)	5.51	5.62	6.08	3.50	1.94	0.50	0.34	0.34	0.24	0.10	*0.26*	*0.18*	*0.14*	*0.11*
tstat	*1.72*	*2.08*	*3.08*	*3.73*	*2.34*	*3.88*	*3.90*	*4.14*	*4.42*	*3.57*	*2.28*	*2.36*	*1.96*	*1.74*
1-R2(TASS)														
Hi-Low(EW)	4.16	4.09	4.18	4.53	5.01	0.11	0.10	0.26	0.08	0.09	0.14	0.09	0.08	0.08
tstat	*4.49*	*4.53*	*4.93*	*5.40*	*6.90*	*3.27*	*3.31*	*5.57*	*3.27*	*4.16*	*5.32*	*4.37*	*4.37*	*4.57*
Hi-Low(VW)	5.90	6.34	6.99	7.50	6.33	0.24	0.14	0.34	0.13	0.13	0.12	0.10	0.08	0.06
tstat	*1.59*	*1.69*	*1.89*	*2.09*	*1.98*	*1.92*	*1.68*	*4.14*	*2.02*	*2.40*	*1.73*	*2.02*	*1.93*	*1.94*

Panel B: Multivariate Regression

	Panel			Fama-MacBeth		
	alpha(% p.a.)	AR	SRAdj	alpha(% p.a.)	AR	SRAdj
	FH7	FH7		FH7	FH7	
SDI(TASS)	3.28	0.10	0.03	*3.94*	*0.10*	*-0.01*
tstat	*4.64*	*5.29*	*1.88*	*2.72*	*3.17*	*0.20*
1-R2(TASS)	4.54	0.14	0.11	4.21	0.14	0.00
tstat	*4.82*	*6.04*	*5.90*	*2.71*	*3.65*	*0.50*

Table 8: Robustness: Drop-out Analysis of Portfolios Sorted Based on the Strategy Distinctiveness Index (1996 - 2008)

Table 8 reports the time series means of the survival rate, in percentage, for quintile portfolios sorted on the Strategy Distinctiveness Index (*SDI*). The portfolios are rebalanced and held for every 3 months, 6 months, and 1-3 years. It also reports the difference between the high and low portfolios and the corresponding t-statistics.

	LowSDIPort	Port2	Port3	Port4	HiSDIPort	Hi-Low	Hi-Lo tstat
3m	95.94	95.42	95.16	95.12	94.60	-1.33	-4.28
6m	91.80	90.95	90.59	90.16	89.35	-2.45	-4.67
1y	83.77	83.09	81.86	81.18	79.86	-3.91	-4.35
2y	69.22	68.82	67.07	66.22	64.77	-4.46	-4.09
3y	56.10	56.51	55.36	53.73	52.28	-3.82	-2.69